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Real-time production planning and control system for job-shop manufacturing: A system dynamics analysis

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A B S T R A C T

Much attention has been paid to production planning and control (PPC) in job-shop manufacturing systems. However, there is a remaining gap between theory and practice, in the ability of PPC systems to capture the dynamic disturbances in manufacturing process. Since most job-shop manufacturing systems operate in a stochastic environment, the need for sound PPC systems has emerged, to identify the discrepancy between planned and actual activities in real-time and also to provide corrective measures. By integrating production ordering and batch sizing control mechanisms into a dynamic model, we propose a comprehensive real-time PPC system for arbitrary capacitated job-shop manufacturing. We adopt a system dynamics (SD) approach which is proved to be appropriate for studying the dynamic behavior of complex manufacturing systems. We study the system's response, under different arrival patterns for customer orders and the existence of various types real-time events related to customer orders and machine failures. We determine the near-optimal values of control variables, which improve the shop performance in terms of average backlogged orders, work in process inventories and tardy jobs. The results of extensive numerical investigation are statistically examined by using analysis of variance (ANOVA). The examination reveals an insensitivity of near-optimal values to real-time events and to arrival pattern and variability of customer orders. In addition, it reveals a positive impact of the proposed real-time PPC system on the shop performance. The efficiency of PPC system is further examined by implementing data from a real-world manufacturer.

1. Introduction

Production planning and control (PPC) in job-shop manufacturing systems is a complex procedure mainly due to the inherent variability of the production process and the stochastic inter-arrival times of customer orders (Stevenson et al., 2005). The inability of traditional PPC systems to capture real-time events and to monitor shop performance by appropriately adjusting the production plan, has raised a question of little correspondence between theory and practice (Cowling and Johansson, 2002; Ouelhadj and Petrovic, 2009). Two crucial issues related to PPC of job-shops include the optimization of production orders to be released to the shop floor, and the optimization of process batch sizes (Browne et al., 1982). The need of providing feedback mechanisms to cope with the existence of real-time events associated with these issues, has been further analyzed by Karmarkar et al. (1992), Takahashi et al. (1994), Pereira and Paulré (2001) and Hopp and Spearman (2001).

Although the research agenda in developing PPC systems that deal with the complexity of job-shops has received much attention, few studies have been undertaken to investigate production ordering and batch sizing under the existence of real-time events. Karmarkar et al. (1992) presented a multi-item batching heuristic which minimizes the queuing delays. Hopp and Spearman (2001) computed optimal batch sizes for serial and parallel batching processes. Corsten et al. (2005) developed a decision-support model for flexibility-driven production order releases under uncertain machine availability. Zhou et al. (2006) developed an Automated Pipeline Inventory and Order Based Production Control System (APIOBPCS)-based controller, to determine the production orders in a hybrid manufacturing and remanufacturing system operating under stochastic conditions. Petrovic et al. (2008) proposed a fuzzy rule-based system, which determines the batch sizes under stochastic processing times and flexible due dates. However, real-time events may cause the scheduled production plans to become obsolete (Gholami and Zandieh, 2009). Cancellations or additional new orders, changes in order priority, processing delays, machine failures are examples of such events, which in combination with the dynamic nature of job-shop manufacturing systems, call for effective real-time PPC mechanisms to identify the changes in

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production plans and to provide corrective measures. One of the key success factors fostering effective implementation of such control mechanisms is the ability of PPC systems to provide information transparency to the decision makers at the time of perceived information need (Tang and Naim, 2004; Towill et al., 2007). The process calls for the delivery of information/data streams, which are related to the objectives of PPC system and derived from internal (e.g. processing times, in-process/on-hand inventories) and external (e.g. customer demand, supplier lead times) sources. The purpose of such streams is to allow the production managers to make and reach informed decisions (Simon, 2006).

In this paper, we develop a comprehensive dynamic model for real-time PPC in an arbitrary capacitated job-shop. The real-time approach reflects the continuous monitoring and adjustment process of the system's state to align it with a desired state. The innovative element of this work is the integration of production ordering and batch sizing control mechanisms into a common PPC system and the investigation of its efficiency in terms of average backlogged orders, work in process inventories (WIP) and tardy jobs for a stochastic multi-machine/multi-product manufacturing environment. We integrate the APIOBPCS (John et al., 1994; Zhou et al., 2006) control theory-based ordering rule and the serial multi-product batch sizing technique proposed by Hopp and Spearman (2001) (from now referred to as HS), into a benchmark PPC system. Both approaches are well-established control mechanisms in providing information transparency through feedback mechanisms (Tang and Naim, 2004). By adapting the APIOBPCS and HS mechanisms to the PPC objectives of job-shop systems and simultaneously by extending the degree of the provided transparency (i.e. the number of information/data streams which are related to the PPC objectives and integrated into the decision making process Towill et al., 2007; Tang and Naim, 2004; Dejonckheere et al., 2004), we propose a real-time PPC system. We study the shop response (product flows, inventories, performance) to the proposed PPC system under existence of real-time events. We consider the arrival pattern of customer orders under a Poisson process and normal distribution, processing times to be randomly distributed over a uniform range of values and routings for the different products to be randomly generated. Cancellations or additional customer orders and machine failures are the real-time event considerations. The dynamic behavior of the shop is obtained by assigning specific values to the control variables of the proposed PPC system. Since the dynamic behavior can be used to evaluate the performance of specific production ordering and batch sizing policies, the PPC system can be viewed as a decision-support system (DSS) for PPC decisions in job-shop manufacturing. By using an optimum-seeking grid search procedure, we determine the near-optimal values of production ordering and batch sizing control variables, which improve shop performance. The results of extensive numerical investigation are statistically examined by using analysis of variance (ANOVA) to identify the sensitivity of near-optimal values to real-time events and to arrival pattern and variability of customer orders. The efficiency of real-time PPC system is compared to that of the benchmark system and it is further examined by implementing data from a real-world refridgeration-bodies manufacturer.

In the field of quantitative research, PPC in stochastic job-shop manufacturing under the existence of real-time events has been methodologically addressed through the development of operations research (OR)-based optimization and heuristic approaches. Optimization approaches have predominantly based on steady-state conditions, ignoring the existence of continuous processes, and reflecting at the very aggregate level the changing environment and dynamic characteristics of a typical job-shop (Mahdavi et al., 2010). Besides, they support decision-makers in PPC issues with a poor flexibility to cope with the multi-period, multi-machine, multi-product, non-linear and stochastic nature of real-world job-shop manufacturing systems. As a result, the PPC related decisions are not based on continuous monitoring of the system's performance to predetermined targets. They are rather based on a traditional plan-based open-loop approach, where the causes for ineffective execution of production plans may be evaluated before initiating a new plan. The optimization models tend to tract very localized corporate decisions (Aytug et al., 2005). By being so local, they are in danger of sub-optimizing to the detriment of the larger system. Although global search approaches, the most commonly used heuristic algorithms such as genetic algorithm (GA) (De Giovanni and Pezzella, 2010), simulated annealing (SA) (Steinhöfel et al., 1999) and particle swarm optimization (Moslehi and Mahnam, 2011), cause often the premature convergence problem and, therefore, lead to less-effective optimization process. Consequently, the heuristics approaches have been improved, leading to the modern intelligence-oriented algorithms; co-evolutionary quantum GA (Gu et al., 2010), hybrid SA with particle swarm optimization (Xia and Wu, 2006), SA with neural networks (Tavakkoli-Moghaddam et al., 2005), fuzzy logic (Petrovic et al., 2008). Despite the advent of fast and inexpensive computing power, the majority of the above-mentioned approaches are coupled with a heavy algorithmic complexity, which makes their application computationally intractable, especially for large-scale real-world applications.

In this paper, in an attempt to face the above-mentioned limitations, we integrate the advantages of OR, control theory and simulation disciplines into a real-time PPC system for job-shop manufacturing, by using the system dynamics (SD) methodological approach. The SD methodology, introduced by Forrester (1961), provides a simple and flexible modeling and simulation framework for decision-making in dynamic industrial management problems (Größler et al., 2008; Georgiadis and Athanasiou, 2010). In contrast to the traditional discrete event simulation-based DSS, the methodology provides an understanding of changes occurring within a manufacturing environment, by focusing on the interaction between physical flows, information flows, delays and policies that create the dynamics of the variables of interest and thereafter searches for policies to improve system performance. Due to its suitability for capturing the dynamic behavior of complex manufacturing systems, we adopt the SD methodology as our tool for modeling and studying PPC mechanisms in job-shop systems.

The rest of the paper is organized as follows. Section 2 presents the objectives and control mechanisms of the proposed real-time PPC system. Section 3 provides the SD model of an arbitrary capacitated job-shop along with its mathematical formulation. By integrating the proposed control mechanisms into the SD model, Section 4 investigates the efficiency of the proposed PPC system in comparison to the benchmark system. The Section also contains the effect of control mechanisms, real-time events and customer order's variability on shop performance and discusses the results obtained by numerical investigation. Section 5 demonstrates a real-world application of the proposed system. The final section contains a brief summary, the new possibilities provided by the proposed approach along with limitations, and potential future research aspects.

2. The proposed PPC system

2.1. Objectives

The proposed PPC system focuses on the improvement of shop performance in terms of the following measures: Average Work in Process (*AverageWIP*), which is the average number of n types of products being processed in $m$workstations; Average Backlogged customer orders (*AverageBacklog*) for n types of products; Average number of tardy jobs (*AverageTardyJobs*) for n types of products (the notation is given in Table 1).

Table 1
Notation list.

Notation	Term
i	Index number of different products
j	Index number of different workstations
$B_i(t)$	Backlogged customer orders regarding product i at time t
$E_i(t)$	Production Orders waiting in the order pool regarding product i at time t
$F_i(t)$	Customer orders remaining in the order file regarding product i at time t
$W_{ij}(t)$	Work in process level of product i in workstation j at time t
$I_i(t)$	Finished goods inventory position of product i at time t
$O_i(t)$	Customer orders for product i at time t
$O_i^c(t)$	New customer orders arrival rate for product i at time t
$O_i^{cN}(t)$	Noise in customer orders for product i at time t
$O_i^p(t)$	Production Orders for product i in workstation j at time t
$D_i(t)$	Delivery rate of product i at time t
$P_{ij}(t)$	Production rate of product i in workstation j at time t
$Q_i(t)$	Work input rate for product i at time t used for batch sizing
$b_i(t)$	Serial process batch size of product i at time t
r_{ij}	Position of workstation j in the routing of product i
$M_i^L(t)$	Total manufacturing lead time of product i at time t
p_{ij}	Processing time of product i in workstation j
$T_i(t)$	Number of tardy jobs regarding product i at time t
u_j	Utilization without setups of workstation j
u_j^*	Optimal utilization of workstation j
$L_j(t)$	Average run length in workstation j at time t
s_{ij}	Time to perform a setup for product i in workstation j
$\bar{s}_j$	Mean time to perform a setup in workstation j
C_j	Production capacity of workstation j
t_w	Work in process adjustment time period
t_i	Finished goods inventory adjustment time period
t_{oht}	Order handling time
$MTBF$	Mean time between failures
$MTTR$	Mean time to repair

$$AverageWIP = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}(t)}{n \cdot m} \tag{1}$$

$$AverageBacklog = \frac{\sum_{i=1}^{n} B_i(t)}{n} \tag{2}$$

$$AverageTardyJobs = \frac{\sum_{i=1}^{n} T_i(t)}{n} \tag{3}$$

The above performance measures are in accordance with surveys, which among others reveal due date adherence and minimization of in-process inventories as two primary objectives for PPC in job-shops (Chiang and Fu, 2009).

2.2. Production ordering control mechanism

APIOBPCS is a control theory-based archetype in which, production orders are given by Eq. (4). It combines the average (or forecasted) customer orders with adjustments that align WIP and finished goods inventories (FGI) with predetermined desired levels in specific time periods. APIOBPCS has been applied to a wide range of dynamic production and inventory management problems and is representative of the ''anchoring and adjustment'' ordering heuristic, suggested by Sterman (1989).

$$\text{Prod. Orders} = \text{Avg. Cust. Orders} + \frac{\text{Desired WIP} - \text{ActualWIP}}{t_w} + \frac{\text{Desired FGI} - \text{ActualFGI}}{t_i} \tag{4}$$

Based on the APIOBPCS archetype, we propose a production ordering mechanism for a typical job-shop system. In particular, we modify the structure of APIOBPCS as follows. The FGI adjustment mechanism, which is of minor importance for job-shop manufacturing, is removed and thereafter, a greater degree of information transparency in terms of tardy jobs is included. The mathematical formulation is provided below:

$$O_i^p(t) = F_i(t) \cdot (1/t_{oht}) + K_w \cdot \left(W_i^*(t) - W_i(t)\right) + K_l \cdot T_i(t) \tag{5}$$

$$W_i^*(t) = E(O_i(t)) \cdot E\left(M_i^L(t)\right) \tag{6}$$

$$E(O_i(t)) = E(O_i(t-1)) + \alpha \cdot [O_i(t) - E(O_i(t-1))] \tag{7}$$

$$E\left(M_i^L(t)\right) = E\left(M_i^L(t-1)\right) + \alpha \cdot \left[M_i^L(t) - E(M_i^L(t-1))\right] \tag{8}$$

$$M_i^L(t) = \sum_{1}^{m} \frac{W_{ij}(t)}{P_{ij}(t)} \tag{9}$$

$$T_i(t) = \max\left\{0, B_i(t) - \left(E(O_i(t)) \cdot \sum_{1}^{m} p_{ij} \middle/ 0.05\right)\right\} \tag{10}$$

By (5) the number of *Production Orders* $\left(O_i^p(t)\right)$ for each product i issued at any time t, is defined as the customer orders remaining in the *Customer Order File* ($F_i(t)$) divided by the order handling time (t_{oht}) (anchor), combined with a fraction K_w ($0 \leqslant K_w \leqslant 1$) of the discrepancy between desired *WIP* $\left(W_i^*(t)\right)$ and actual *WIP* (WIP adjustment), and a fraction K_l ($0 \leqslant K_l \leqslant 1$) of the number of tardy jobs ($T_i(t)$) (we consider the desired value of tardy jobs equal to zero). The actual *WIP* for each product i, is the sum of WIP in all workstations $\left(W_i(t) = \sum_{j=1}^{m} W_{ij}(t)\right)$, while the desired WIP level is defined in (6) by the expected customer orders ($E(O_i(t))$) and the average manufacturing lead time $\left(E\left(M_i^L(t)\right)\right)$. Expected customer orders and average manufacturing lead time are defined in (7) and (8) respectively, as a first-order exponential smoothing of the actual *Customer Orders* ($O_i(t)$) and manufacturing lead time $\left(M_i^L(t)\right)$ of product i at time t respectively, with smoothing factor α. Manufacturing lead time is defined in (9) as the time needed to eliminate WIP from all workstations, based on the current production rate ($P_{ij}(t)$).

The number of tardy jobs ($T_i(t)$) appeared in (5), is defined in (10) as the non-negative difference between the actual level of *Backlog File* ($B_i(t)$) and its desired value. The definition of the desired value of *Backlog File* is related to due date adherence. In particular, the definition of due dates is a procedure demanding precise estimation of job flow-times. Flow-times, however, are subject to a number of factors including product routing, customer order quantities, current level of shop loading and number of jobs in the queue of bottleneck workstation. In fact, the flow-time prediction problem is considered to be the crux of the due date assignment problem (Baykasoglu et al., 2008). The literature provides several due date assignment methods. Methods which incorporate job characteristics (e.g. total work content, common slack, number of operations) are justified to perform better compared to those which ignore them (Conway et al., 1967); ''Total Work Content'' (based on processing time) and ''Process Plus Waiting'' (based on job waiting time) are examples of such methods (Baykasoglu et al., 2008; Sha et al., 2007). In job-shop manufacturing systems a product can spend up to 90–95% of its total throughput time waiting to be processed, while only 5–10% is spent on actual processes and transfer times (Stommel, 1976; Bradt, 1983). Consequently, the desired values of *Backlog File* for each product i are defined as the product of expected customer orders ($E(O_i(t))$) and $\sum_{1}^{m} p_{ij}/0.05$.

Fig. 1(a) illustrates the causal loop diagram of the proposed control mechanism. In SD discipline, causal loop diagrams serve as preliminary sketches of causal hypotheses, simplify the representation of a model and represent the major feedback mechanisms (Sterman, 2000). These mechanisms are either negative feedback (balancing) or positive feedback (reinforcing) loops. A negative feedback loop exhibits goal-seeking behavior; after a disturbance, the system seeks to return to an equilibrium situation. In a positive feedback loop an initial disturbance leads to further change, suggesting the presence of an unstable equilibrium. To improve

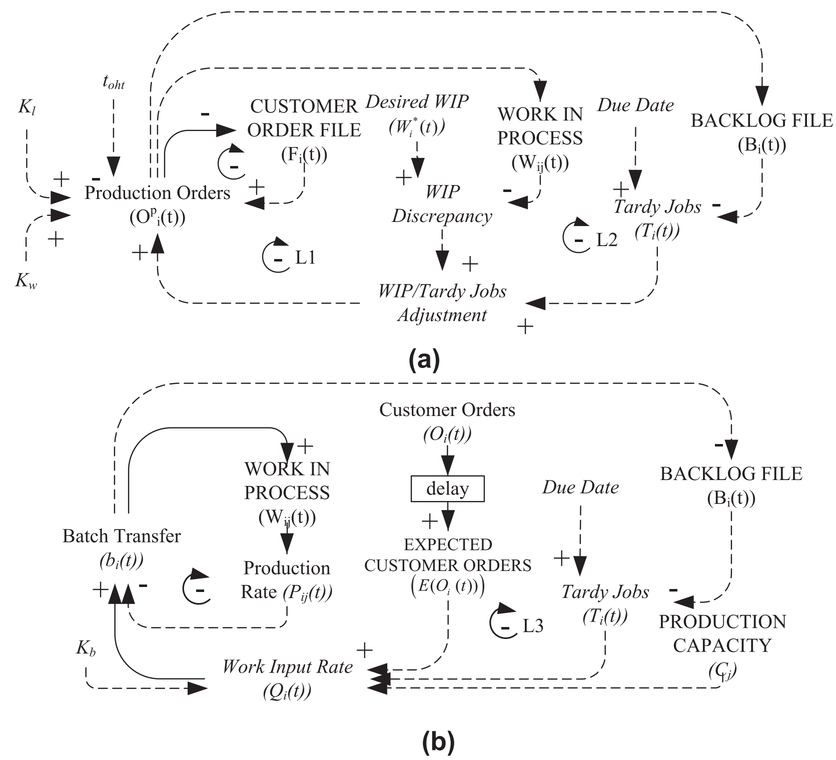


Fig. 1. Causal loop diagrams for the proposed PPC mechanisms.

appearance and distinction among the variables in the causal loop diagram, we changed the letter style according to the variable type; stock variables are written in capital letters, flow variables in small plain letters and auxiliary variables in small italic letters. The arrows (influence lines) represent the relations among variables. The direction of influence lines displays the direction of the effect while the sign "+" or "−" exhibits the sign of the effect. A "+" sign dictates that the variables change in the same direction; a "−" sign dictates the opposite. In particular, the structure of production ordering mechanism illustrated in Fig. 1(a), is based on the adjustment of actual WIP and tardy jobs to their desired values, represented by the negative feedback loops *L1* (*Work In Process, WIP Discrepancy, WIP/Tardy Jobs Adjustment, Production Orders, Work In Process*) and *L2* (*Tardy Jobs, WIP/Tardy Jobs Adjustment, Production Orders*, *Backlog File, Tardy Jobs)* respectively.

2.3. Batch sizing control mechanism

Numerous batch sizing techniques, employed in a wide range of different real-world problem domains, are suggested by the literature. However, one of the major limitations of these models is the assumption of deterministic demand and processing times (Jans and Degraeve, 2008). The HS technique is a well-established batch sizing rule to control the flow of materials through a multi-product/multi-machine manufacturing system operating in a stochastic environment. Based on the arrival rate of new customer orders along with queue characteristics (setup times, processing times and capacity), the suggested procedure dynamically determines run lengths at each workstation. These run lengths manage the capacity utilization by controlling the setup frequency. The batch sizing rule results in significant reduction of throughput time and throughput variability. In particular, the HS technique aims at minimizing the cycle time at the workstation j along with the balancing of run lengths across all products. We extend the control mechanism of HS by incorporating the number of tardy jobs, to achieve a greater degree of information transparency. We replace the demand rate (D_i) in HS by the work input rate of product i at time t ($Q_i(t)$), which is defined by the anchoring and adjustment heuristic (Sterman, 1989) as the expected customer orders ($E(O_i(t))$) (anchor) plus a fraction K_b ($0 \leqslant K_b \leqslant 1$) of the number of tardy jobs ($T_i(t)$) (tardy jobs adjustment):

$$Q_i(t) = E(O_i(t)) + K_b T_i(t) \tag{11}$$

The optimal batch size of product i at time t ($b_i(t)$) is defined in accordance to the HS technique by the Eqs. (12) and (13), which are applied to the first workstation j as indicated by the routing (explained in Section 3):

$$b_i(t) = \frac{L_j(t) - s_{ij}}{p_{ij}} \tag{12}$$

$$L_j(t) = \begin{cases} \frac{\sum_1^n Q_i(t) s_{ij} p_{ij}}{u_j^*(t) - u_j(t)} + \bar{s}_j, & u_j^*(t) < 1 \\ \sum\limits_1^n Q_i(t) s_{ij} p_{ij} + \bar{s}_j, & u_j^*(t) = 1 \end{cases} \tag{13}$$

where, $L_j(t)$ is the average run length, s_{ij} the product's setup time, p_{ij} the processing time, $\bar{s}_j$ the mean setup time and $u_j^*(t)$ the optimal workstation utilization which is defined in (14) as the ratio of the workload to the *Production Capacity* (C_j). A good approximation of $u_j^*(t)$ can be derived by $u_j^*(t) = \sqrt{u_j(t)}$ (Hopp and Spearman, 2001) where, $u_j(t) = \sum_1^n Q_i(t) p_{ij}$.

$$u_j^*(t) = \frac{\sum_1^n Q_i(t)\left(1 + \frac{s_{ij}}{b_i(t)}\right)}{C_j} \tag{14}$$

Fig. 1(b) illustrates the causal loop diagram of the batch sizing control mechanism. The structure of batch sizing mechanism is based on the adjustment of actual tardy jobs to their desired values, represented by the negative feedback loop *L3* (*Tardy Jobs, Work Input Rate, Batch Transfer, Backlog File, Tardy Jobs).*

3. Modeling of a typical job-shop manufacturing system

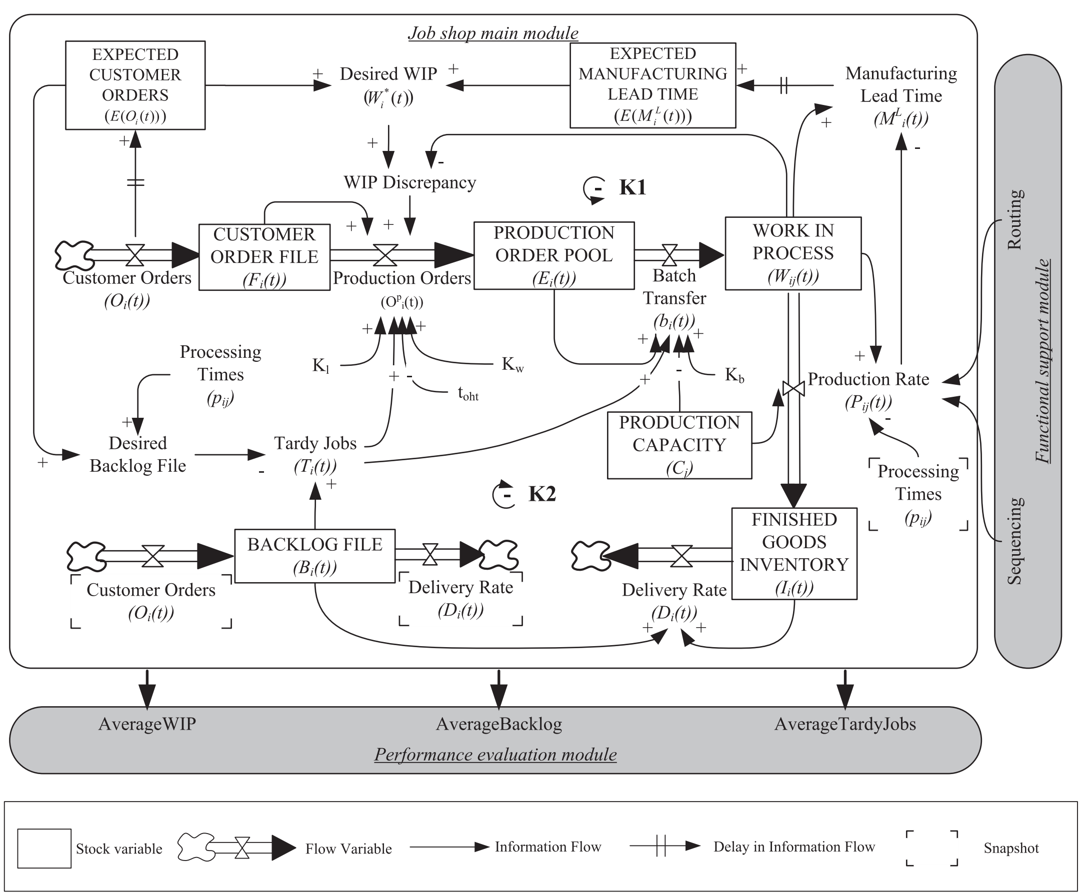
3.1. Job-shop considerations

We consider an arbitrary capacitated job-shop manufacturing system of m workstations indexed by $j = 1,2,\ldots,m$, providing n types of products indexed by $i = 1,2,\ldots,n$ through random routings. Each product i, requires k operations ($k \in \mathbb{Z}$). The position of workstation j in the routing of product i is given by $r_{ij} = (1,2,\ldots,k)$. Since any given product may have to visit the same workstation more than once during its production process (recirculation), a set of routing positions r_{ij} is created for any combination (i,j). For instance, in the simple case where the routing of an arbitrary product i is 1, 2, 3, 1, 4 the position of workstation $j = 4$ in the routing of product i is given by $r_{i4} = \{5\}$, while for workstation $j = 1$ is given by $r_{i1} = \{1,4\}$. The adopted dispatching rule is the shortest processing time (SPT), which has proved to be effective in minimizing mean flow-time and mean tardiness under highly loaded shop floor conditions (Blackstone et al., 1982).

The system incorporates the following standard assumptions, as reported by the job-shop manufacturing literature (Conway et al., 1967; Baker, 1974): (1) each workstation can perform only one operation at a time on a product (job); (2) each workstation is constantly available for assignment, without partition into shifts or days and without being kept idle while work is waiting; (3) jobs are simple sequences of operations (i.e. no assembly is allowed) and they consist of strictly ordered operation sequences; (4) only one workstation is capable of performing a given operation (i.e. there is no alternate available routing); (5) once an operation is started in a workstation, it must be completed without interruption before another operation can begin in that workstation; (6) a job can be in process on at most one operation at any time point (i.e. no overlap scheduling and no splitting is allowed); (7) each time a changeover is required at any workstation, the necessary setup time is assumed to be sequence-independent; (8) transfer times between workstations are assumed to be negligible.

3.2. SD model

We develop the SD model of an arbitrary job-shop consisting of five workstations ($m = 5$) and producing up to six different types of products ($n \leqslant 6$). In SD discipline, the model is usually presented as a stock-flow diagram that captures the model structure and the interrelationships among the variables (Sterman, 2000). The stock-flow diagram is translated into a system of differential equations, which is then solved via numerical simulation. The embedded mathematical equations are divided into stock equations (state equations), which integrate the net flow into a stock, and flow equations (rate equations), defining the inflows and outflows among the stocks as functions of time. Fig. 2 illustrates the generic stock-flow diagram. The SD model is developed using the Powersim®2.5c software package and consists of three modules: job-shop main module; functional support module (which contains the routing and sequencing functions); and performance evaluation module (which



Loop K1: Negative Feedback Loop (*Production Ordering Mechanism*): Work In Process → Production Orders → Production Order Pool → Batch Transfer → Work In Process.

Loop K2: Negative Feedback Loop (*Batch Sizing Mechanism*): Tardy Jobs → Production Orders → Production Order Pool → Batch Transfer → Work In Process → Production Rate → Finished Goods Inventory → Delivery Rate → Backlog File → Tardy Jobs.

Fig. 2. Generic stock and flow diagram of the system under study.

provides the performance dynamics). The model includes 6 state array variables (*Customer Order File, Production Order Pool, Work In Process, Finished Goods Inventory, Backlog File* and *Production Capacity*), 6 array flows (*Customer Orders, Production Orders, Order Release, Production Rate, Batch Transfer* and *Delivery Rate*) and a considerable number of auxiliary variables and array constants, employed mainly for the determination, for each product i, of the routing and dispatching priorities (212 array auxiliary variables, 26 array constants).

3.3. Mathematical formulation

In SD models, the stock and flow perspective represents time as unfolding continuously; events can happen at any time; change can occur continuously. The general mathematical representation of stocks and flows is given by the following equations:

$$Stock(t) = \int_{t_0}^{t} [Inflow(t) - Outflow(t)]dt + Stock(t_0) \tag{15}$$

$$Inflow(t) = f(Stock(t), E(t), P);$$
$$Outflow(t) = g(Stock(t), E(t), P) \tag{16}$$

where, E any exogenous variables and P system parameters.

The production procedure starts whenever a customer enquiry is set and an equivalent order enters the shop. New *Customer Orders* ($O_i(t)$) for each product i, arrive at any time t and are backlogged in two files: *Backlog File* ($B_i(t)$) and *Customer Order File* ($F_i(t)$). The former is used as a measure of total amount of orders being in the shop at any time t, and is given by the state equation (17):

$$B_i(t) = \int_0^t [O_i(t) - D_i(t)]dt + B_i(0) \tag{17}$$

where, $D_i(t)$ is the *Delivery Rate* of finished products to customers. *Customer Orders* remain in the *Customer Order File* ($F_i(t)$) until they are translated into *Production Orders* $\left(O_i^p(t)\right)$, according to the employed production ordering mechanism. The total amount of customer orders for product i kept in the *Customer Order File* at time t, is defined by the following state equation:

$$F_i(t) = \int_0^t [O_i(t) - O_i^p(t)]dt + F_i(0) \tag{18}$$

The new *Production Orders* $\left(O_i^p(t)\right)$ are waiting in a *Production Order Pool*, until they are released to the shop floor. For each product i, the production orders are released in batches ($b_i(t)$) according to the employed SPT dispatching rule, and are transferred in front of the first workstation indicated by the routing ($r_{ij} = 1$). The total amount of orders waiting in the *Production Order Pool* at time t is given by the state equation (19):

$$E_i(t) = \int_0^t \left[O_i^p(t) - b_i(t)\right]dt + E_i(0) \tag{19}$$

We consider that process batches ($b_i(t)$) are equal to transfer batches. Hence, *Work In Process* level ($W_{ij}(t)$) in each workstation is increased by both incoming production orders and transfer batches while it is depleted by *Production Rate* ($P_{ij}(t)$), as follows:

$$W_{ij}(t) = \begin{cases} \int_0^t b_i(t)dt + \sum\limits_{r_{ij}=2}^{k} \left(\int_0^t b_{i,r_{ij}}(t)dt\right) - \sum\limits_{r_{ij}=1}^{k} \left(\int_0^t P_{ij,r_{ij}}(t)dt\right) \\ \quad +W_{ij}(0), \quad r_{ij} = 1 \\ \sum\limits_{r_{ij}=2}^{k} \left(\int_0^t b_{ij,r_{ij}}(t)dt\right) - \sum\limits_{r_{ij}=1}^{k} \left(\int_0^t P_{ij,r_{ij}}(t)dt\right) + W_{ij}(0), \\ \quad r_{ij} = 2, \ldots, k \end{cases} \tag{20}$$

The *Production Rate* ($P_{ij}(t)$) of product i in workstation j, is defined by the processing times (p_{ij}) and is constrained by both *Production Capacity* (C_j) and WIP availability:

$$P_{ij}(t) = \left(\frac{1}{p_{ij}} | C_j > 0, W_{ij}(t) > 0\right), \quad \forall\{i,j\} \tag{21}$$

After being processed in workstation $j(r_{ij} = z | z = 1, 2, \ldots, k-1)$, the batch of each product ($b_i(t)$) is transferred to the next workstation according to the routing ($r_{ij} = z+1 | z = 1, 2, \ldots, k-1$). After the completion of the required processes at the last workstation $r_{ij} = k$, products are moved to the warehouse (*Finished Goods Inventory*) where they remain until the point of delivery to the customers. The level of *Finished Goods Inventory* of product i at time t is defined by the state equation (22):

$$I_i(t) = \int_0^t [P_{ij,r_{ij}=k}(t) - D_i(t)]dt + I_i(0) \tag{22}$$

4. Numerical investigation and discussion of results

We investigate the efficiency of the real-time PPC system by conducting four sets of numerical experiments. In the first, we search for the near-optimal values of the proposed PPC system, as represented by control variables K_w and K_l (for production ordering mechanism) and K_b (for batch sizing mechanism). In the second, we compare the effectiveness of the proposed real-time PPC system to the one provided by the benchmark PPC system. In both sets of experiments, the system's performance is examined under the absence of real-time events. The impact of real-time events on near-optimal values K_w, K_l and K_b is examined in the third experiment. Cancellations or additional customer orders and machine failures are the real-time event considerations. *Customer Orders* ($O_i(t)$) are defined by the following equation:

$$O_i(t) = O_i^c(t) + O_i^{cN}(t) \tag{23}$$

where, $\left(O_i^c(t)\right)$ is the arrival rate of new customer orders while $\left(O_i^{cN}(t)\right)$ is a "noise" effect enabled in the third set of experiments, to describe the common practice of customers either to cancel existing orders or to set additional ones. The arrival of new customer orders $\left(O_i^c(t)\right)$ is described by a Poisson process with the parameter λ being equal to *Mean Orders* (units/day) for each product *i*. *Mean Orders* is examined under three levels of value, which are defined in equivalence to capacity utilization; 4 units/day (60%), 5 units/day (75%), 6 units/day (90%). The appearance of "noise" events $\left(O_i^{cN}(t)\right)$ is randomly generated with a probability of appearance (*NoiseProbability*) equal to 7.5% and a magnitude expressed as percentage of *Mean Orders* (*NoiseMagnitude*). *NoiseMagnitude* follows a uniform distribution with limits equal to ±0.5. Machine failures are described by a Poisson process with mean-time-between-failures (*MTBF*) equal to 1 day and the required mean-time-to-repair (*MTTR*) equal to 0.1 days. Finally in the fourth experiment, we study the effect of customer orders variability on the system's performance (the special settings are given in Subsection 4.4). The rest of the settings are as follows.

Order handling time (t_{oht}) is equal to 1 day, production capacity is equal to 40 machine hours/per day, machine setup time is equal to 1 machine hour, while raw materials inventory and warehouse capacity for WIP inventories and FGI are assumed to be infinite. Processing times (p_{ij}) per product i on workstation j follow a uniform distribution with lower (upper) limits equal to 0.08 (0.96) machine hours, while routings for the different products are randomly generated. Simulation horizon is equal to 25 working days to capture the system's behavior out of the transient region. We conduct 20 repetitive simulation runs for each experiment to test for alternative generators of random numbers, concerning the processing times and the products' routing. Throughout numerical investigation, the mean values of control variables and performance measures obtained at the end of the simulation horizon are considered as the output of the relative simulation runs.

We checked the model's validity by conducting tests suggested by the SD literature (Sterman, 2000; Barlas, 1996). Firstly, we tested the model's dimensional consistency. Then we conducted extreme condition tests, checking whether the model behaves realistically even under extreme PPC policies. For example, we checked that if the *Batch Size* is extremely large, then the *Production Order Pool* is depleted immediately or if there is no *Customer Orders*, production ceases. Finally, integration error tests were conducted. We used the integration method Euler, since the Runge–Kutta method should be avoided in models with random disturbances (Sterman, 2000). Integrating time step (dt) is equal to 3 minutes, significantly shorter than the shortest time constant in the model. The model was further validated using data from a real-world manufacturer (see Section 5).

4.1. The effect of control mechanisms on system's performance

We use the SD model in conjunction with an optimum-seeking grid search procedure with grid resolution equal to 0.1, to determine the near-optimal values of control variables (K_w, K_l and K_b), which leads to $(11^3)^*(20) = 26620$ simulation runs for each level of value of *Mean Orders* (capacity utilization). Table 2 shows the near-optimal values K_w, K_l and K_b for the different *Mean Orders* values, along with their coefficient of variation (shown in brackets), which optimize the performance measures.

With regard to production ordering mechanism, from Table 2 it turns out that the near-optimal values K_w and K_l are almost the same for capacity utilization 60%, 75% and 90%. Interestingly, the insensitivity of near-optimal production ordering policy to the customer orders, identified through the above analysis, is not coincidental. The same insensitivity to 20% increase and decrease of *Mean Orders* (or 15% change in capacity utilization) was also observed in a number of individual simulation runs not showing for brevity. Although it is in principle risky to generalize on the basis of numerical examples, the fact that: (i) the proposed production ordering mechanism is driven by the discrepancy between the desired and actual levels of WIP along with the number of tardy jobs and (ii) the magnitude of the production orders is proportional to the observed discrepancy, leads to the conjecture that the near-optimal values K_w and K_l are indeed robust to moderate changes in customer orders. This is an extremely positive property of the proposed production ordering mechanism, since accurate forecasts of customer orders are quite difficult to obtain in an on-demand job-shop production environment.

With regard to batch sizing mechanism, Table 2 shows that the near-optimal values K_b decrease as *Mean Orders* increases. This observation reveals the dominance of anchor mechanism (as expressed by expected customer orders $E(O_i(t))$ in equation (11)), in defining the optimal batch sizes.

Furthermore, the non-zero values of control variables K_w, K_l and K_b justify the positive impact of the proposed PPC mechanisms in improving the overall shop performance. In particular, the comparative study of simulation results reveals that under near-optimal values K_w, K_l and K_b the *AverageBacklog*, *AverageWIP* and *AverageTardyJobs* are improved by 4.3%, 2.2% and 4.4% respectively, compared to the case of $K_w = K_l = K_b = 0$.

Table 2
Near-optimal values and coefficient of variation of control variables.

Mean Orders (cap. utilization)	Control variable		
	K_w	K_l	K_b
4 (60%)	0.26 [0.350]	0.58 [0.143]	0.72 [0.110]
5 (75%)	0.27 [0.325]	0.56 [0.141]	0.58 [0.103]
6 (90%)	0.26 [0.342]	0.56 [0.143]	0.34 [0.093]

4.2. Comparative study

To compare the effectiveness of the proposed PPC system to the benchmark system, we firstly identify the optimal values of control variables $K'_w = 1/t_w$ (used in WIP adjustment) and $K'_i = 1/t_i$ (used in FGI adjustment) incorporated in the APIOBPCS mechanism (Eq. (4)). Thereafter, by performing a similar analysis to that of Section 4.1, we determine the near-optimal values of K'_w being equal to 0.14 for the case of 75% capacity utilization and 0.13 (0.14) for the case of 60% (90%) capacity utilization. The control variable K'_i was not found to affect the system performance. We conduct a numerical experiment for each capacity utilization level (60%, 75% and 90%). Throughout experimentation, the values of control variables for both proposed and benchmark PPC system are set equal to the respective near-optimal values. A comparative study of the mean values of performance measures reveals that the proposed PPC system improves the *AverageBacklog* by 7.8%, the *AverageWIP* by 4.6% and the *AverageTardyJobs* by 7.6%, compared to the case of benchmark system.

Another positive property of the proposed real-time PPC system is its ability to cope with uncertainty issues, as expressed by its robustness to sudden changes in customer orders. Fig. 3 illustrates the evolution of *AverageBacklog* for both benchmark and proposed PPC systems (under near-optimal values K'_w, K'_i and K_w, K_l, K_b). It illustrates also the evolution of *AverageBacklog* for a pulse increase of *Mean Orders* by 10% and by 20% respectively. In both cases the pulse change occurs in the 14th working day, to capture the system's behavior after having achieved an equilibrium condition. Despite the same transient period for the two systems (5.3 days), we observe a more stable behavior for the case of proposed PPC system; under a 10% (20%) pulse impose, the *AverageBacklog* increases by 2.14% (4.6%) in case of proposed PPC system while by 12.78% (16.56%) in case of benchmark system. Similar observations are also obtained for the cases of *AverageWIP* and *AverageTardyJobs*.

4.3. The effect of real-time events on system's performance

We conduct a sensitivity analysis of the three performance measures (*AverageBacklog*, *AverageWIP*, *AverageTardyJobs*) to 5

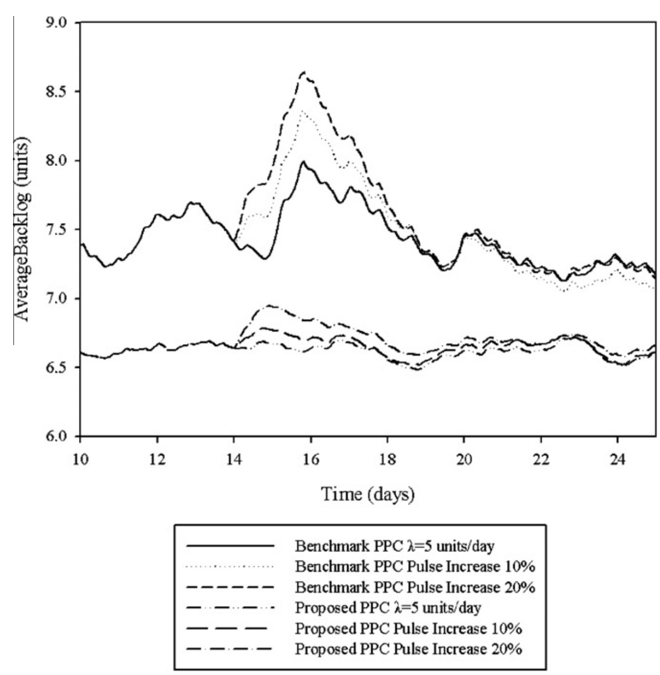


Fig. 3. Time response of *AverageBacklog* to pulse impose in *Mean Orders* under near-optimal policies.

Table 3
Control factors and sets of level in the third set of experiments.

Control factors	Sets of level		
Mean Orders (units/day)	4	5	6
NoiseProbability (%)	5	7.5	10
NoiseMagnitude	0.5		1.5
MTBF (days)	0.5		1
MTTR (days)	0.1		0.2

"noise" (control) factors (*Mean Orders*, *NoiseProbability*, *NoiseMagnitude*, *MTBF*, *MTTR*), to examine the impact of real-time disturbances related to customer orders and machine failures on shop performance. The control factors are examined under different sets of level shown in Table 3. The experimental design consists of a full factorial design with $3^2 \times 2^3 = 72$ combinations of the control factors. In each combination the values of control variables K_w, K_l and K_b are set equal to the near-optimal values shown in Table 2. The total number of simulation runs is equal to $(72) \times (20) = 1440$.

Table 4 illustrates the results of ANOVA for the dependence of performance measures to the control factors, up to third order interactions. The *p-value* column reflects the lowest significance levels that would lead to rejection of the null hypothesis that the control factor or interaction does not affect the system's performance measures (at the 5% significance level). The *partial Eta-squared* $\left(\eta_p^2\right)$ (PES), reflects the significance of the control factor compared to the error's significance; the higher the PES value of a control factor, the higher the magnitude of its effect on the response variable.

A thorough examination of the results shown in Table 4, leads to the following observations regarding the sensitivity of the performance measures and subsequently of the near-optimal PPC policies:

- The main effect of the control factors *NoiseProbability*, *NoiseMagnitude*, *MTBF* and *MTTR* does not affect significantly the near-optimal values K_w, K_l and K_b.
- As expected, the main effect of *Mean Orders* affects significantly only the near-optimal values of K_b, which also reflects the sensitivity of *AverageBacklog* to the *Mean Orders*. This observation, in conjunction to the insensitivity of *AverageTardyJobs*, reveals that changes in *Mean Orders* value affect the waiting time of customer orders in the *Backlog File* but do not have an impact on the average number of tardy jobs.
- The second order interaction of *Mean Orders* and *NoiseProbability* affects significantly only the near-optimal values of K_b.
- The sensitivity of K_b control variable reflects the importance of the tardy jobs adjustment mechanism, shown in equation (11), for effective implementation of the proposed real-time PPC system.

4.4. The effect of customer orders variability on system's performance

We assume that for each product *i*, new customer orders $\left(O_i^c(t)\right)$ arrive in a normally distributed pattern with mean value μ and standard deviation σ being equal to *Mean Orders* (units/day) and *Orders SD* (units/day) respectively. To achieve comparable results with those obtained by the first set of experiments, the system's performance is examined under the absence of real-time events and under the same levels of value for *Mean Orders* (4, 5 and 6 units/day). In each case *Orders SD* is examined under three levels of value, which are defined in relation to the coefficient of variation (= *MeanOrders**CV). To investigate the robustness of the proposed control policies in a range of high variability, the levels of CV value are selected to be equal to 0.2 ± 20%, i.e. 0.16, 0.2 and 0.24. By performing a similar analysis to that of Subsection 4.1, we determine the near-optimal values K_w, K_l and K_b for each level of *Orders SD* value, leading to a total number of $(11^3)^*(20)^*(3)^*(3) = 239{,}580$ simulation runs.

The comparative analysis of the results, not shown for brevity, leads to the following interesting results regarding the sensitivity of the proposed PPC mechanisms to the variability of customer orders:

- The near-optimal values K_w, K_l and K_b are not significantly affected by the distribution of the new customer orders. Consequently, we recognize the insensitivity of the near-optimal PPC policies to the arrival pattern of new customer orders.
- The near-optimal values K_w, K_l and K_b are almost the same for the different levels of value of *Orders SD* and therefore of CV. This observation reveals the strong robustness of the proposed PPC mechanisms to the variability of customer orders.

5. The case of a real-world manufacturer

The proposed real-time PPC system is implemented in a real-world manufacturer, operating in the region of Central Macedonia in Greece. The manufacturer produces tailor-made refrigeration bodies (six main types) for commercial vehicles, according to the individual needs and technical specifications of each customer. The manufacturing operations take place in a network of four workstations while in a fifth one the finished bodies are fitted to the vehicles. The probability function for both customer orders and machine failures was defined by using data obtained from the manufacturer. The customer orders arrive in a Poisson process with mean value 20 vehicles/month, while the machine mean-time-to-failure is described by the exponential distribution with mean value 4 hours and mean-time-to-repair equal to 20 minutes.

We identified the near-optimal values of control variables; $K_w = 0.2$, $K_l = 0.5$ and $K_b = 0.7$. We observed that under the near-optimal values of K_w, K_l and K_b, the average number of tardy jobs are decreased by 4.3%, the average backlogged orders by 4.4% and the average WIP levels by 2.2% in comparison to the case of $K_w = K_l = K_b = 0$.

However, the manufacturer could not operate always under the near-optimal values. Changes in the external environment such as necessity for higher safety stock and arrival of new customer orders with higher priority were events calling for different PPC policies. Fig. 4 illustrates the *AverageBacklog* (a), *AverageWIP* (b) and *AverageTardyJobs* (c) performance measures for various combinations of K_l and K_b, when K_w is equal to its near-optimal value.

The results shown in Fig. 4 revealed the range of values of K_l and K_b which holistically improved the system's performance ($K_l = 0.45 - 0.6$, $K_b = 0.6 - 0.75$). These results were further used in a "what–if" analysis, to study the effect of different PPC policies on system's performance and also to quantify the effect caused by the divergence from near-optimal PPC policies. Specifically, if K_l is increased by 20% from its near-optimal value ($K_l = 0.6$) then the *AverageBacklog* increases by 1.8%, the *AverageWIP* by 1.1% and *AverageTardyJobs* by 1.7%. An equivalent increase in the value of K_b ($K_b = 0.84$) leads to increase in the *AverageBacklog* by 1.1%, in the *AverageWIP* by 0.6% and in the *AverageTardyJobs* by 1.2%. In case of K_l (K_b) is equal to its near-optimal value, the same analysis revealed that the system's performance was holistically improved under the range of values 0.15–0.35 (0.18–0.35) for K_w and 0.65–0.8 (0.5–0.65) for K_b (K_l).

Although the proposed PPC system calls for continuous monitoring, for practical reasons the manufacturer applied a monitoring in a daily basis. Fig. 5 exhibits the evolution of *AverageBacklog* under three different review periods; continuous (3 minutes), one

Table 4
Results of ANOVA (*p*-values and Partial Eta Squared) for the effects of *Mean Orders*, *NoiseProbability*, *NoiseMagnitude*, *MTBF* and *MTTR* on the near-optimal values of control variables.

Factor-interaction	AverageBacklog						AverageWIP						AverageTardyJobs					
	K_w		K_l		K_b		K_w		K_l		K_b		K_w		K_l		K_b	
	p-value	PES	*p*-value	PES	*p*-value	PES	*p*-value	PES	*p*-value	PES	*p*-value	PES	*p*-value	PES	*p*-value	PES	*p*-value	PES
Mean Orders	.119	.006	.144	.002	.005	.021	.155	.007	.222	.006	.251	.006	.457	.003	.614	.002	.396	.004
NoiseProbability	.892	.000	.440	.001	.630	.000	.678	.000	.743	.000	.356	.002	.919	.000	.391	.001	.536	.001
NoiseMagnitude	.760	.000	.259	.003	.659	.000	.483	.001	.072	.006	.395	.001	.801	.000	.285	.002	.699	.000
MTBF	.583	.001	.418	.001	.774	.000	.408	.001	.191	.003	.772	.000	.743	.000	.607	.001	.487	.001
MTTR	.331	.002	.566	.001	.348	.002	.717	.000	.784	.000	.586	.001	.322	.002	.573	.001	.356	.002
Mean Orders * NoiseProbability	.249	.006	.627	.002	.015	.017	.086	.010	.223	.006	.003	.023	.262	.005	.668	.002	.021	.016
Mean Orders * NoiseMagnitude	.626	.002	.919	.000	.712	.001	.711	.001	.916	.000	.779	.001	.635	.002	.870	.001	.773	.001
Mean Orders * MTBF	.094	.010	.233	.006	.940	.000	.137	.008	.214	.006	.325	.005	.107	.009	.241	.006	.973	.000
Mean Orders * MTTR	.089	.010	.246	.006	.069	.011	.084	.010	.070	.011	.352	.004	.093	.010	.199	.006	.054	.012
NoiseProbability * NoiseMagnitude	.242	.003	.990	.000	.275	.002	.068	.007	.524	.001	.386	.002	.220	.003	.978	.000	.286	.002
NoiseProbability * MTBF	.353	.002	.448	.001	.534	.001	.652	.000	.929	.000	.680	.000	.330	.002	.399	.001	.460	.001
NoiseProbability * MTTR	.198	.003	.457	.001	.895	.000	.261	.003	.151	.004	.451	.001	.209	.003	.468	.001	.922	.000
NoiseMagnitude * MTBF	.134	.009	.132	.005	.311	.002	.356	.002	.591	.001	.423	.001	.133	.009	.107	.005	.311	.002
NoiseMagnitude * MTTR	.638	.000	.873	.000	.819	.000	.408	.001	.640	.000	.737	.000	.708	.000	.834	.000	.721	.000
MTBF * MTTR	.679	.000	.217	.003	.129	.005	.675	.000	.712	.000	.285	.002	.689	.000	.226	.003	.130	.005
Mean Orders * NoiseProbability * NoiseMagnitude	.126	.008	.912	.000	.931	.000	.128	.004	.796	.001	.519	.003	.119	.009	.889	.000	.961	.000
Mean Orders * NoiseProbability * MTBF	.665	.002	.119	.009	.810	.001	.302	.005	.069	.011	.180	.007	.695	.001	.134	.008	.847	.001
Mean Orders * NoiseProbability * MTTR	.352	.004	.868	.001	.300	.005	.226	.006	.985	.000	.172	.007	.387	.004	.807	.001	.325	.005
Mean Orders * NoiseMagnitude * MTBF	.270	.005	.056	.012	.167	.007	.150	.008	.149	.002	.055	.012	.265	.005	.096	.001	.191	.007
Mean Orders * NoiseMagnitude * MTTR	.722	.001	.672	.002	.127	.008	.909	.000	.921	.000	.273	.005	.731	.001	.642	.002	.102	.009
Mean Orders * MTBF * MTTR	.699	.001	.648	.002	.151	.012	.591	.002	.668	.002	.192	.007	.739	.001	.650	.002	.055	.012
NoiseProbability * NoiseMagnitude * MTBF	.741	.000	.118	.005	.296	.002	.895	.000	.122	.005	.325	.002	.676	.000	.109	.005	.276	.002
NoiseProbability * NoiseMagnitude * MTTR	.271	.002	.378	.002	.206	.003	.602	.001	.526	.001	.658	.000	.314	.002	.386	.002	.189	.003
NoiseProbability * MTBF * MTTR	.602	.001	.634	.000	.843	.000	.352	.002	.824	.000	.864	.000	.659	.000	.683	.000	.836	.000
NoiseMagnitude * MTBF * MTTR	.463	.001	.578	.001	.451	.001	.948	.000	.601	.001	.722	.000	.498	.001	.604	.001	.424	.001

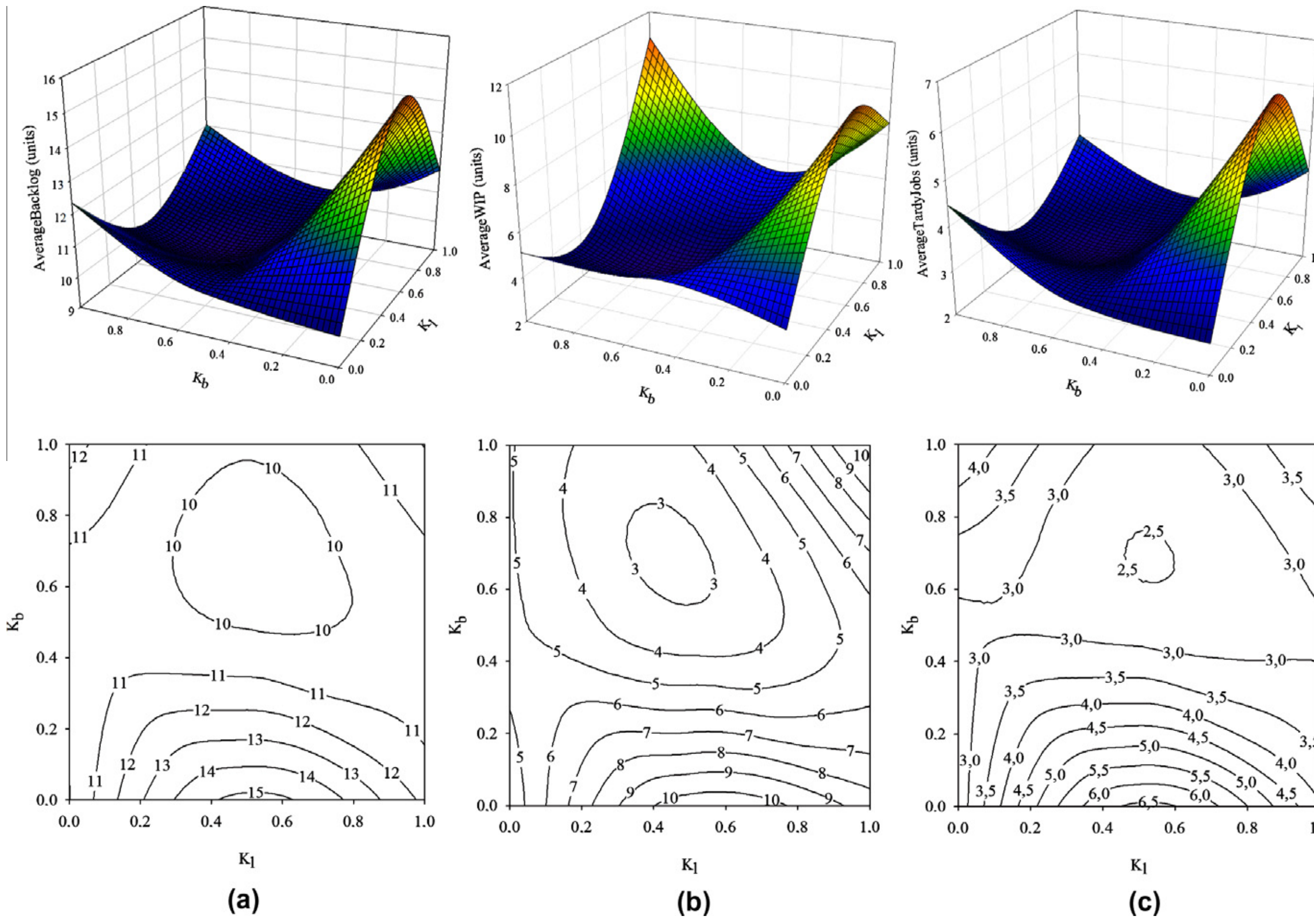


Fig. 4. Impact of K_b and K_l on the system's performance ($K_w = 0.2$).

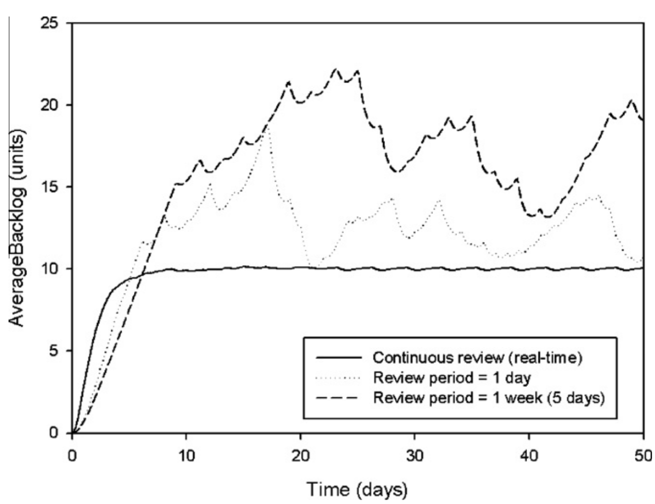


Fig. 5. Dynamic behavior of *AverageBacklog* under different review periods of the production plan.

day (8 hours), and one week (40 hours). We observe the impact of longer review periods on the level of *AverageBacklog*.

6. Summary and future research

In this paper, we developed control mechanisms for production ordering and batch sizing in a stochastic capacitated arbitrary job-shop system. Through the integration of these mechanisms into a common system, we proposed a real-time PPC system with an objective to improve the shop performance in terms of average work in process, average backlogged orders and average number of tardy jobs. Employing an interdisciplinary approach, the PPC mechanisms are described by a stock-flow structure, which provides the capability to capture the dynamics of material, product and information flows under the existence of real-time events and also to incorporate them in PPC related decisions.

The proposed approach provides the following possibilities to the decision makers: (i) decision making in real-time mode on the magnitude of shop flows (product, material, production/customer orders), (ii) continuous monitoring of the system's actual state (work-in-process/finished goods inventories, backlog of production/customer orders), (iii) ability to integrate real-time disturbances (machine failures, cancellations of customer orders/additional orders) into PPC-related decisions, and (iv) dynamic adaptation of desired system's states (desired work-in-process, desired finished goods inventory, desired customer orders backlog) to changes in the shop environment. In addition, the employed interdisciplinary approach provides the ability to consider the non-linear, non-stationary and uncertain nature of job-shop manufac turing. Although the results of our analysis are based on a five-workstation/six-product job-shop, the findings can be generalized for job-shop manufacturing systems, given that the number of workstations in the shop floor does not crucially influence the relative performance of production control rules (Baker, 1974; Blackstone et al., 1982).

The proposed real-time PPC mechanisms face limitations. The continuous monitoring and adjustment process of the system's state requires the use of real-time controllers, which in automated production systems are integrated in their IT infrastructure. However, in a more traditional job-shop manufacturing environment, the controllers are human-driven and consequently the monitoring and adjustment of the production plan practically takes place in longer time periods, resulting in suboptimal shop performances. The results of numerical investigation also revealed the need to further extend the proposed PPC mechanisms in order to better anticipate the system's sensitivity for both incoming customer orders and their interaction with "noise" events in the manufacturing environment.

The results presented in this paper certainly do not exhaust the possibilities of investigating all the factors affecting the dynamic performance of job-shop manufacturing systems. For example, it is worthwhile studying how dynamic capacity planning and workforce planning policies affect the optimal production ordering and batch sizing policies. Moreover, the integration of cost elements into the proposed control mechanisms may have added-value in the development of more comprehensive real-time PPC systems.

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